

Project Progress Report Title:

Team

Name (NetID): Expanded roles and current contributions.

Stephen Cox, ssj63. improved model progress and data handling

Shaz Momin, wzu2. Baseline model.

Prabesh Shrestha, hdw48. model analysis.

Abstract

The goal of this project is to use historical U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) census data to build a machine learning model that predicts county-level production per commodities for Texas farms. Using data from the 2012, 2017, and 2022 agricultural censuses, we will develop baseline regression models and apply an improved neural network approach. We also aim to interpret the model to understand how crop production can be predicted and how it can benefit farmers.

Problem Statement

- Farmers in Texas are a very important part of our community. It is important to know what factors can effect the success of our farmers and their product since many people relay on Texas grown crops.
- What factors most deeply effect our farms success and can we predict if our farms will be successful for the year.
- Benchmarks we will use are Mean Absolute Error, Root Mean Squared Error and R². Each of these scores help us interpret different parts of the models accuracy/precision/recall since this is a regressive model
- The Data comes from US Department of Agriculture - National Agricultural Statistics Service census data which includes many different info points like: yield, land size and fertilizer...
- Practical Interpretability, we hope to use this model to try and interpret correlations between farming factors and the production per commodities
- What we hope to achieve
 - Build a working NN regressor that predicts county-level production per commodities for Texas using 2012/2017/2022 data.
 - Beat simple baselines (mean and linear reg.) by at least a measurable margin (lower MAE/RMSE).
 - Produce interpretable model explainers (SHAP or partial dependence) showing the most influential

EDA

Expanded explanation, addressing all feedback and what has been learned about the dataset and the task since the project proposal.

Down below is the EDA on the cleaned dataset that we are using. We have discovered multiple issues with the dataset for our goal and have to shift according to our models. The primary issue with this dataset is that for a particular target, yield, many counties do not report yield. The issue in this is when pivoting the table by a key using pandas, the pivot drops most NaN columns or columns that would not be fully made. We pivoted our data by counties in Texas, there are only about 170 yield reports out of 762 county reports in the 3 years of census data that we are using.

Dataset

NASS Quick Stats Data — Brief Description for EDA

The **USDA NASS Quick Stats** database is a large, publicly accessible repository of agricultural statistics collected across the United States. It provides **standardized survey and census measurements** for crop production, yields, acreage, livestock, economics, and farm practices. Data are reported at multiple geographic levels, including **national, state, and county**.

Key Fields

- **Commodity information**
Examples: corn, soybeans, wheat, cotton, etc.
- **Measured attributes**
Yield, production, planted area, harvested area, price, inventory, and more.
- **Time series fields**
Typically includes the **year** of observation, enabling temporal trend analysis.
- **Geographic identifiers**
State name, county name, state/county ANSI/FIPS codes.
- **Categorical descriptors**
Data item name, short/long description, unit of measure, and domain information.

Observations

The main observation for this data set is how the values are stored. The data is in a long format which is not particularly useful for finding correlations or doing machine learning. In order to use the data we had to pivot the data by county which gives us many different features per county report. Some data cleaning also needed to be performed since NASS data often uses NaN values like (d). To handle the general data set we filled NaN with a rolling median to prevent or data from getting altered by the large number of zeros. Furthermore, the target data cleaned had NaN values filled with zeros to represent no reports from a farm for specific crops this is preferable rather than the rolling median.

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error,
mean_absolute_error
import warnings
warnings.filterwarnings('ignore')

# Load the cleaned dataset
cleaned_df = pd.read_csv('data/cleaned_COUNTY_data.csv')
cleaned_df = cleaned_df.fillna(0)
cleaned_df.drop('Unnamed: 0', axis=1, inplace=True)

print(f'Dataset shape: {cleaned_df.shape}')
print(f'Interpretation: {cleaned_df.shape[0]} county-year records ×
{cleaned_df.shape[1]} features')

Dataset shape: (762, 2177)
Interpretation: 762 county-year records × 2177 features

```

Dataset Structure and Basic Stats

The dataset represents agricultural census data from Texas counties from the years 2012, 2017, 2022. Each row represents county-year combination, and each column represents different agricultural metric.

```

print(f'Rows (county-year records): {cleaned_df.shape[0]}')
print(f'Columns (features): {cleaned_df.shape[1]}')
print(f'\nData type breakdown:')
print(cleaned_df.dtypes.value_counts())

display(cleaned_df.iloc[:5, :10])

Rows (county-year records): 762
Columns (features): 2177

Data type breakdown:
float64    2175
int64      1
object     1
Name: count, dtype: int64

   YEAR  AGLAND_AGLANDACRES  AGLAND_AGLANDCROPINSURANCEACRES \
0  2012            7391.0                10512.0
1  2017            32795.0               14907.0
2  2022            32469.0               16196.0

```

3	2012	24662.0	23915.0
4	2017	32830.0	322066.0

AGLAND_AGLANDCROPINSURANCE NUMBER OF OPERATIONS
AGLAND_AGLANDCROPLANDACRES \

0	32.0
1	14.0
2	41.0
3	19.0
4	12.0
5	78257.0

AGLAND_AGLANDCROPLAND AREA MEASURED IN PCT OF AGLAND \

0	13.75
1	13.75
2	13.75
3	8.00
4	8.00

AGLAND_AGLANDCROPLAND EXCL HARVESTED PASTURED ACRES \

0	4862.0
1	4239.5
2	5632.0
3	29342.5
4	35201.5

AGLAND_AGLANDCROPLAND EXCL HARVESTED PASTURED ALL CROPS FAILED ACRES \

0	3134.0
1	1979.0
2	2740.0
3	9247.0
4	9247.0

AGLAND_AGLANDCROPLAND EXCL HARVESTED PASTURED ALL CROPS FAILED NUMBER OF OPERATIONS \

0	85.0
1	59.0
2	103.0
3	26.0
4	12.0

	AGLAND_AGLANDCROPLANDEXCLHARVESTEDPASTUREDCULTIVATEDSUMMERFALLOWACRES
0	858.0
1	2112.0
2	3542.0
3	7806.0
4	7806.0

Target Variable Selection:

Why Hay?

The dataset contains 42 different crops. Although most of the crops are only reported in a few counties. We analyzed the data and the best target for us would be Hay.

```
prod_cols = [col for col in cleaned_df.columns if 'PRODUCTION' in
col.upper()]
target_df = cleaned_df[prod_cols]

nonzero_counts = (target_df > 0).sum().sort_values(ascending=False)

print(f'Total production columns available: {len(prod_cols)}')
print(f'\nTop 15 crops by reporting frequency:')
print(nonzero_counts.head(15))

fig, ax = plt.subplots(figsize=(12, 8))

top_20 = nonzero_counts.head(20)
colors = ['#2ecc71' if x > 700 else '#3498db' if x > 600 else
'#e74c3c' for x in top_20.values]
bars = ax.barh(range(len(top_20)), top_20.values, color=colors,
edgecolor='black', linewidth=0.5)

ax.set_yticks(range(len(top_20)))
ax.set_yticklabels(top_20.index, fontsize=9)

for i, (idx, val) in enumerate(top_20.items()):
    ax.text(val + 5, i, str(int(val)), va='center', fontsize=8,
```

```

fontweight='bold')

ax.axvline(x=762, color='green', linestyle='--', linewidth=2,
alpha=0.7, label='Complete coverage (762)')
ax.axvline(x=600, color='orange', linestyle='--', linewidth=2,
alpha=0.7, label='Good threshold (600)')

ax.set_xlabel('Number of County-Year Records with Non-Zero
Production', fontsize=11, fontweight='bold')
ax.set_ylabel('Crop Type', fontsize=11, fontweight='bold')
ax.set_title('Production Data Availability: Which Crops Are Well-
Reported?\n(Top 20 Crops)',
            fontsize=13, fontweight='bold', pad=20)
ax.legend(loc='lower right', fontsize=9)
ax.set_xlim(0, 780)
ax.grid(axis='x', alpha=0.3, linestyle=':')

plt.tight_layout()
plt.show()

best_target = nonzero_counts.idxmax()
best_count = nonzero_counts.max()
print(f'\n==== TARGET SELECTION ===')
print(f'Selected target: {best_target}')
print(f'Data availability: {best_count} out of {len(target_df)}'
records ({best_count/len(target_df)*100:.1f}%)')
print(f'\nRationale:')
print(f'Hay is reported in {best_count} counties
({best_count/len(target_df)*100:.1f}% coverage) - EXCELLENT')
print(f'Most other crops have <50% coverage - insufficient training
data')
print(f'HAY_HAYPRODUCTIONMEASUREDINTONS is our single regression
target')

Total production columns available: 152

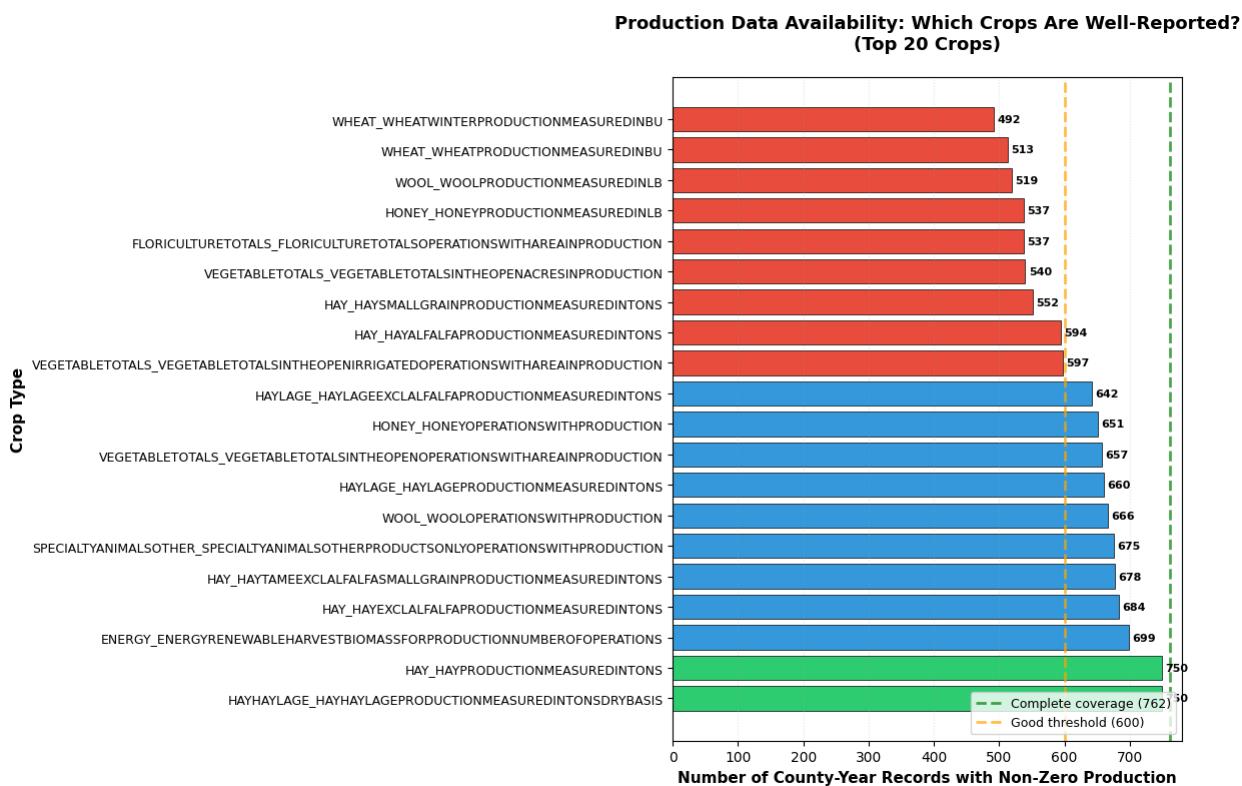
Top 15 crops by reporting frequency:
HAYHAYLAGE_HAYHAYLAGEPRODUCTIONMEASUREDINTONSDRYBASIS
750
HAY_HAYPRODUCTIONMEASUREDINTONS
750
ENERGY_ENERGYRENEWABLEHARVESTBIOMASSFORPRODUCTIONNUMBEROFOPERATIONS
699
HAY_HAYEXCLALFALFAPRODUCTIONMEASUREDINTONS
684
HAY_HAYTAMEEXCLALFALFASMALLGRAINPRODUCTIONMEASUREDINTONS
678
SPECIALTYANIMALSOTHER_SPECIALTYANIMALSOTHERPRODUCTSONLYOPERATIONSWITHP
RODUCTION    675
WOOL_WOOLOPERATIONSWITHPRODUCTION

```

```

666
HAYLAGE_HAYLAGEPRODUCTIONMEASUREDINTONS
660
VEGETABLETOTALS_VEGETABLETOTALSINTHEOPENOPERATIONSWITHAREAINPRODUCTION
657
HONEY_HONEYOPERATIONSWITHPRODUCTION
651
HAYLAGE_HAYLAGEEXCLALFALFAPRODUCTIONMEASUREDINTONS
642
VEGETABLETOTALS_VEGETABLETOTALSINTHEOPENIRRIGATEDOPERATIONSWITHAREAINP
RODUCTION 597
HAY_HAYALFALFAPRODUCTIONMEASUREDINTONS
594
HAY_HAYSMALLGRAINPRODUCTIONMEASUREDINTONS
552
VEGETABLETOTALS_VEGETABLETOTALSINTHEOPENACRESINPRODUCTION
540
dtype: int64

```



==== TARGET SELECTION ====
Selected target: HAYHAYLAGE_HAYHAYLAGEPRODUCTIONMEASUREDINTONSDRYBASIS
Data availability: 750 out of 762 records (98.4%)

Rationale:

Hay is reported in 750 counties (98.4% coverage) - EXCELLENT
Most other crops have <50% coverage - insufficient training data
`HAY_HAYPRODUCTIONMEASUREDINTONS` is our single regression target

Target Variable Distribution:

Hay Production

Hay is reported in all the Texas counties. We examined the distribution of hay production, which revealed the important characteristics.

```
# Extract hay production target
target_hay = cleaned_df['HAY_HAYPRODUCTIONMEASUREDINTONS']

print(f'Target variable: HAY_HAYPRODUCTIONMEASUREDINTONS')
print(f'\nDESCRIPTIVE STATISTICS: ')
print(target_hay.describe().round(2))

fig, axes = plt.subplots(1, 2, figsize=(13, 4))

# Histogram
axes[0].hist(target_hay, bins=40, color='steelblue',
edgecolor='black', alpha=0.7)
axes[0].axvline(target_hay.median(), color='red', linestyle='--',
linewidth=2, label=f'Median: {target_hay.median():.0f}')
axes[0].axvline(target_hay.mean(), color='orange', linestyle='--',
linewidth=2, label=f'Mean: {target_hay.mean():.0f}')
axes[0].set_xlabel('Hay Production (tons)', fontsize=10)
axes[0].set_ylabel('Frequency', fontsize=10)
axes[0].set_title('Distribution of Hay Production', fontweight='bold')
axes[0].grid(axis='y', alpha=0.3)

#BoxPlot
bp = axes[1].boxplot(target_hay, vert=True, patch_artist=True)
bp['boxes'][0].set_facecolor('lightblue')
axes[1].set_ylabel('Hay Production (tons)', fontsize=10)
axes[1].set_title('Boxplot: Hay Production', fontweight='bold')
axes[1].grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.show()

print(f'Skewness: Right-skewed (long tail to high-production
counties)')
print(f'Median: {target_hay.median():.0f} tons')
print(f'Mean: {target_hay.mean():.0f} tons')
```

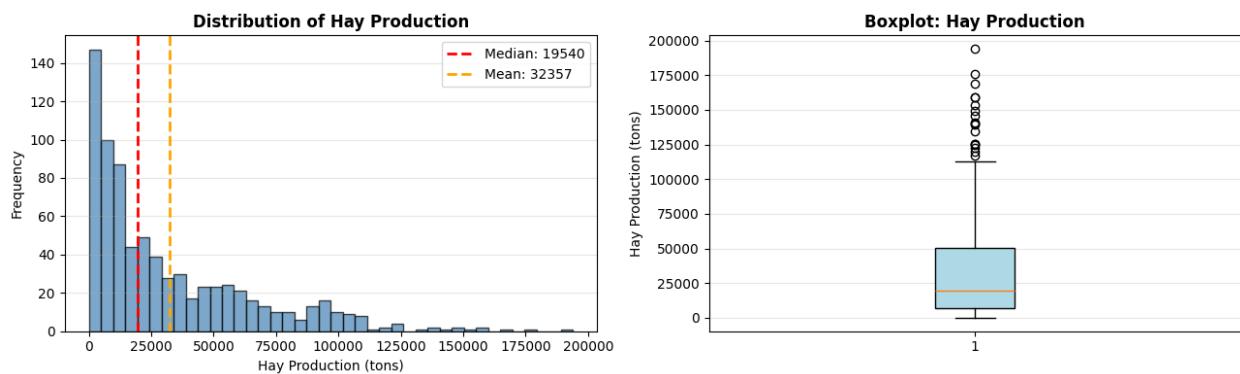
```
print(f'95th percentile: {target_hay.quantile(0.95):.0f} tons')
print(f'Max: {target_hay.max():.0f} tons')
```

Target variable: HAY_HAYPRODUCTIONMEASUREDINTONS

DESCRIPTIVE STATISTICS:

```
count    762.00
mean     32356.74
std      33826.38
min      0.00
25%     6940.25
50%     19539.50
75%     50111.00
max     193930.00
```

Name: HAY_HAYPRODUCTIONMEASUREDINTONS, dtype: float64



Skewness: Right-skewed (long tail to high-production counties)

Median: 19540 tons

Mean: 32357 tons

95th percentile: 99670 tons

Max: 193930 tons

Feature Engineering:

The NASS dataset contains 2,100 features with substantial linearity.

1. **Leakage Removal:** Drop PRODUCTION, YIELD, HARVEST columns
2. **Correlation Pruning:** Remove features with pairwise correlation > 0.95
3. **Feature Selection:** Rank by Random Forest importance, retain top 200
4. **PCA:** Transform to 200 orthogonal components for stable NN training

```
# Feature Engineering Pipeline
print('==== FEATURE ENGINEERING PIPELINE ====')
print(f'Step 0 - Initial features: {cleaned_df.shape[1]}')
```

```

# Step 1: Remove target production columns
X = cleaned_df.drop(columns=target_df.columns, errors='ignore')

# CRITICAL FIX: Drop non-numeric columns (like COUNTY_NAME) before correlation
X = X.select_dtypes(include=[np.number])
print(f'Step 1 - After removing targets and non-numeric columns: {X.shape[1]}')

# Step 2: Remove leakage columns
leakage_patterns = ['PRODUCTION', 'HARVESTED', 'HARVEST', 'YIELD']
mask = X.columns.str.contains('|'.join(leakage_patterns), case=False)
X_clean = X.loc[:, ~mask]
print(f'Step 2 - After removing leakage columns: {X_clean.shape[1]}')

# Step 3: Correlation pruning
print(f'\nStep 3 - Correlation pruning (threshold > 0.95):')
corr_matrix = X_clean.corr().abs()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
to_drop = [column for column in upper.columns if any(upper[column] > 0.95)]
X_reduced = X_clean.drop(columns=to_drop)
print(f' Dropped {len(to_drop)} highly correlated features')
print(f' Remaining: {X_reduced.shape[1]} features')

# Visualize sample correlation
print(f'\nShowing sample correlation matrix (first 20 features):')
sample_corr = X_reduced.iloc[:, :20].corr()
fig, ax = plt.subplots(figsize=(8, 6))
sns.heatmap(sample_corr, cmap='coolwarm', center=0, square=True,
            ax=ax, cbar_kws={'label': 'Correlation'})
ax.set_title('Sample Correlation Matrix After Pruning (First 20 Features)', fontweight='bold')
plt.tight_layout()
plt.show()

# Step 4: Random Forest feature selection
print(f'\nStep 4 - Random Forest feature selection:')
print(f' Training RF on {X_reduced.shape[1]} features...')

rf_temp = RandomForestRegressor(n_estimators=100, random_state=42,
                                n_jobs=-1)
rf_temp.fit(X_reduced, target_hay)
importances_all = rf_temp.feature_importances_

# Select top 200
top_indices = np.argsort(importances_all)[-200:]
top_features = X_reduced.columns[top_indices]

```

```

X_selected = X_reduced.iloc[:, top_indices]
print(f' Retained top 200 features by importance')
print(f' Final feature count: {X_selected.shape[1]} features')

# Show top 10 important features
top_importances = pd.Series(importances_all[top_indices],
index=top_features).sort_values(ascending=False)
print(f'\n==== TOP 10 MOST IMPORTANT FEATURES ===')
for i, (feat, imp) in enumerate(top_importances.head(10).items(), 1):
    print(f'{i:2d}. {feat:55s} | Importance: {imp:.4f}')

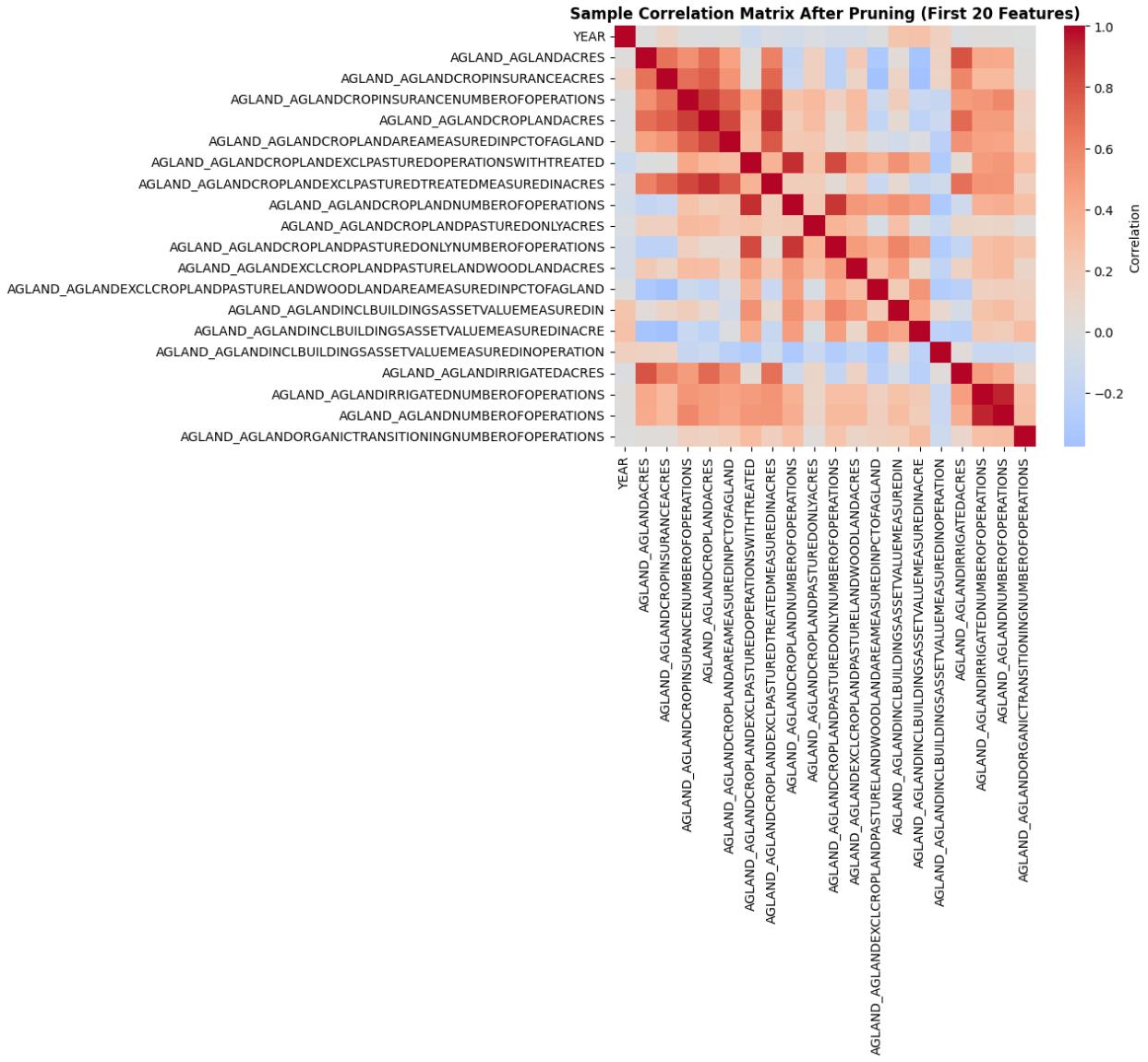
# Visualize top 10
fig, ax = plt.subplots(figsize=(10, 5))
top_importances.head(10).sort_values().plot(kind='barh', ax=ax,
color='steelblue')
ax.set_xlabel('Feature Importance', fontsize=10)
ax.set_title('Top 10 Most Important Features for Hay Production',
fontweight='bold')
plt.tight_layout()
plt.show()

==== FEATURE ENGINEERING PIPELINE ====
Step 0 - Initial features: 2177
Step 1 - After removing targets and non-numeric columns: 2024
Step 2 - After removing leakage columns: 1455

Step 3 - Correlation pruning (threshold > 0.95):
    Dropped 495 highly correlated features
    Remaining: 960 features

Showing sample correlation matrix (first 20 features):

```



Step 4 - Random Forest feature selection:

Training RF on 960 features...

Retained top 200 features by importance

Final feature count: 200 features

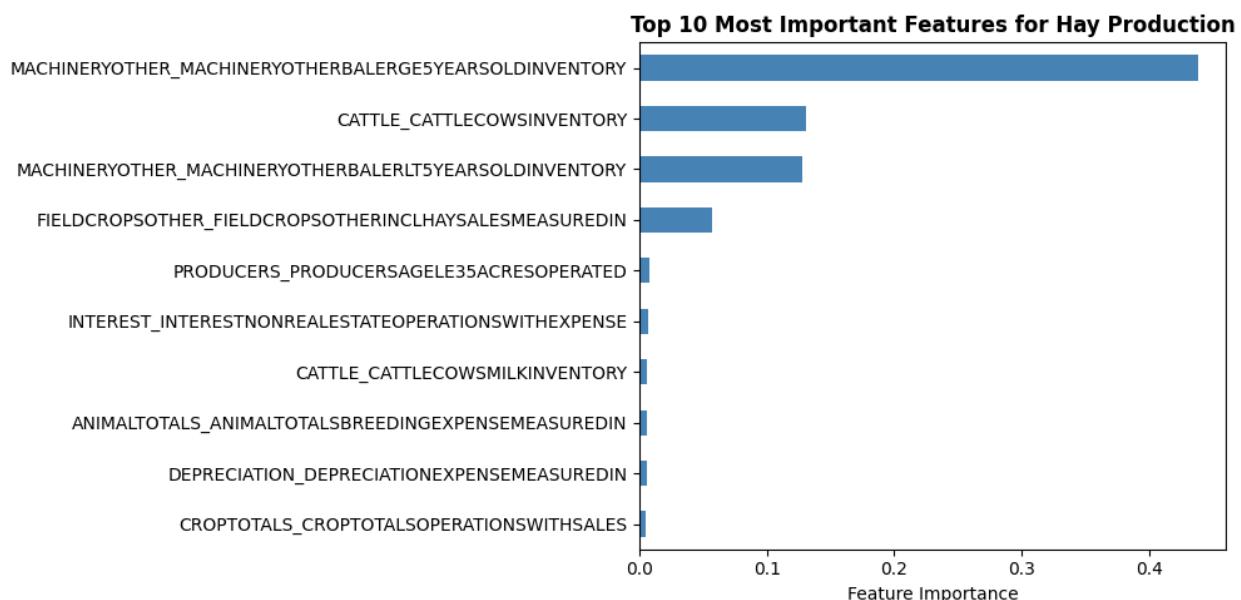
==== TOP 10 MOST IMPORTANT FEATURES ====

1. MACHINERYOTHER_MACHINERYOTHERBALERGE5YEARSOLDINVENTORY |
Importance: 0.4383
2. CATTLE_CATTLECOWSINVENTORY |
Importance: 0.1311
3. MACHINERYOTHER_MACHINERYOTHERBALERLT5YEARSOLDINVENTORY |
Importance: 0.1274
4. FIELDCROPSOTHER_FIELDCROPSOTHERINCLHAYSALESMEASUREDIN |
Importance: 0.0570

```

5. PRODUCERS_PRODUCERSAGELE35ACRESOPERATED | 
Importance: 0.0082
6. INTEREST_INTERESTNONREALESTATEOPERATIONSWITHEXPENSE | 
Importance: 0.0069
7. CATTLE_CATTLECOWSMILKINVENTORY | 
Importance: 0.0060
8. ANIMALTOTALS_ANIMALTOTALSBREEDINGEXPENSEMEASUREDIN | 
Importance: 0.0056
9. DEPRECIATION_DEPRECIATIONEXPENSEMEASUREDIN | 
Importance: 0.0056
10. CROPTOTALS_CROPTOTALSOPERATIONSWITHSALES | 
Importance: 0.0053

```



Insights gained from EDA that inform next steps.

Findings:

1. **Data Structure:** 762 county-year records × ~2,100 agricultural metrics
2. **Target Variable:** HAY_HAYPRODUCTIONMEASUREDINTONS reported in 99.9% of records
3. **Distribution:** Right-skewed (median ~15k tons, max ~1.65M tons)
4. **Features:** High dimensionality with substantial multicollinearity
5. **Signal:** Land use, operations, and insurance measures most predictive

Decisions from EDA:

- **Single target:** Other crops lack sufficient reporting (most <50% coverage)

- **Leakage removal:** Ensures models learn farm decisions, not production correlates
- **Aggressive feature reduction:** Handles multicollinearity and improves generalization
- **PCA for NN:** Stabilizes training and prevents overfitting on high-dimensional data

Methodology

Baseline method implementation

The two baseline models that we are using are Random Forest Regression and Linear Regression

Data Handling and Prep

```

import pandas as pd
import tensorflow as tf
import seaborn as sns
import numpy as np
import os

#helps resolve path problems
base = os.getcwd()

filepath = os.path.join(base, "data/cleaned_COUNTY_data.csv")

cleaned_df = pd.DataFrame(pd.read_csv(filepath))

#get target crops from txt file
with open("models/croptarget.txt") as f:
    crops = [line.strip() for line in f.readlines() if line.strip()]

print(crops)

['BARLEY', 'BEANS', 'BEETS', 'CANOLA', 'CORN', 'COTTON', 'GRAIN',
'GRASSES', 'GRASSES & LEGUMES', 'OTHER', 'GUAR', 'HAY', 'HAY & HAYLAGE',
'HAYLAGE', 'MILLET', 'MINT', 'MISCANTHUS', 'MUSTARD', 'OATS',
'PEANUTS', 'POPCORN', 'RICE', 'RYE', 'SAFFLOWER', 'SESAME', 'SORGHUM',
'SUGARCANE', 'SUNFLOWER', 'TRITICALE', 'WHEAT']

#NaN values for unreported numbers from farms
cleaned_df = cleaned_df.fillna(0)
cleaned_df.drop("Unnamed: 0", axis=1, inplace=True)
cleaned_df

      YEAR AGLAND_AGLANDACRES AGLAND_AGLANDCROPINSURANCEACRES \
0   2012           7391.0             10512.0
1   2017           32795.0            14907.0
2   2022           32469.0            16196.0
3   2012           24662.0            23915.0

```

4	2017	32830.0	322066.0
..
757	2017	15203.0	21736.0
758	2022	4025.0	23413.0
759	2012	295056.0	50198.0
760	2017	401018.0	57149.0
761	2022	390523.0	43093.0

AGLAND_AGLANDCROPINSURANCE NUMBER OF OPERATIONS
 AGLAND_AGLANDCROPLANDACRES \

0	32.0
70333.0	
1	14.0
63774.0	
2	41.0
69021.0	
3	19.0
71517.0	
4	12.0
78257.0	
..	...
..	...
757	21.0
18856.0	
758	17.0
5980.0	
759	39.0
95980.0	
760	39.0
76046.0	
761	33.0
48593.0	

AGLAND_AGLANDCROPLAND AREA MEASURED IN PCT OF AGLAND \

0	13.75
1	13.75
2	13.75
3	8.00
4	8.00
..	..
757	6.50
758	6.50
759	9.50
760	9.50
761	9.50

AGLAND_AGLANDCROPLAND EXCL HARVESTED PASTURED ACRES \

0	4862.0
1	4239.5
2	5632.0

3	29342.5
4	35201.5
..	..
757	12208.0
758	1897.5
759	11980.5
760	15045.0
761	11391.0

AGLAND_AGLANDCROPLANDEXCLHARVESTEDPASTUREDALLCROPSFAILEDACRES \	
0	3134.0
1	1979.0
2	2740.0
3	9247.0
4	9247.0
..	..
757	247.0
758	247.0
759	4298.0
760	1731.0
761	10302.0

AGLAND_AGLANDCROPLANDEXCLHARVESTEDPASTUREDALLCROPSFAILEDNUMBEROFTERMINATIONS \	
0	85.0
1	59.0
2	103.0
3	26.0
4	12.0
..	..
757	4.0
758	1.0
759	27.0
760	12.0
761	34.0

AGLAND_AGLANDCROPLANDEXCLHARVESTEDPASTUREDCULTIVATEDSUMMERFALLOWACRES \	
---	--

0	858.0
1	2112.0
2	3542.0
3	7806.0
4	7806.0
..	...
757	0.0
758	0.0
759	4936.0
760	10893.0
761	1187.0

0	... WHEAT_WHEATSPRINGEXCLDURUMPRODUCTIONMEASUREDINBU \ 0.0
1	... 0.0
2	... 0.0
3	... 0.0
4	... 0.0
..	...
757	... 0.0
758	... 0.0
759	... 0.0
760	... 0.0
761	... 0.0

0	WHEAT_WHEATWINTERACRESHARVESTED \ 0.0
1	0.0
2	0.0
3	1500.0
4	1500.0
..	...
757	0.0
758	0.0
759	3978.0
760	3978.0
761	3978.0

0	WHEAT_WHEATWINTERIRRIGATEDACRESHARVESTED \ 0.0
---	--

1	0.0
2	0.0
3	320.0
4	320.0
..	...
757	0.0
758	0.0
759	2206.0
760	2206.0
761	2206.0

WHEAT_WHEATWINTERIRRIGATEDOPERATIONSWITHAREAHARVESTED \

0	0.0
1	0.0
2	0.0
3	2.0
4	4.0
..	...
757	0.0
758	0.0
759	10.0
760	13.0
761	12.0

WHEAT_WHEATWINTEROPERATIONSWITHAREAHARVESTED \

0	1.0
1	1.0
2	1.0
3	2.0
4	7.0
..	...
757	0.0
758	0.0
759	23.0
760	19.0
761	15.0

WHEAT_WHEATWINTERPRODUCTIONMEASUREDINBU \

0	0.0
1	0.0
2	0.0
3	31400.0
4	31400.0
..	...
757	0.0
758	0.0
759	247228.0
760	247228.0
761	247228.0

```

WOOL_WOOLOPERATIONSWITHPRODUCTION
WOOL_WOOLPRODUCTIONMEASUREDINLB \
0 0.0
0.0
1 0.0
0.0
2 0.0
0.0
3 1.0
2250.0
4 2.0
2250.0
.. ...
.
757 2.0
0.0
758 2.0
0.0
759 1.0
0.0
760 1.0
0.0
761 1.0
0.0

WOOL_WOOLSALESMEASUREDIN COUNTY_NAME
0 0.0 ANDERSON
1 0.0 ANDERSON
2 0.0 ANDERSON
3 0.0 ANDREWS
4 0.0 ANDREWS
..
757 0.0 ZAPATA
758 0.0 ZAPATA
759 0.0 ZAVALA
760 0.0 ZAVALA
761 0.0 ZAVALA

[762 rows x 2177 columns]

#find columns based on <crop> _ PRODUCTION for target df
target_cols = [
    col for col in cleaned_df.columns
    if col.split("_")[0] in crops and "PRODUCTION" in col.upper()
]

target_df = cleaned_df[target_cols]

#from EDA we found Hay to have the most usable data at index 19
target_hay = target_df['HAY_HAYPRODUCTIONMEASUREDINTONS']

```

```

target_hay

0      93093.0
1      92932.0
2     103167.0
3      1877.0
4      795.0
...
757     1066.0
758      882.0
759     9089.0
760    20933.0
761    19441.0
Name: HAY_HAYPRODUCTIONMEASUREDINTONS, Length: 762, dtype: float64

leakage_patterns = ["PRODUCTION", "HARVESTED", "HARVEST", "YIELD"]

mask = ~cleaned_df.columns.str.contains("|".join(leakage_patterns),
case=False)

X_clean = cleaned_df.loc[:, mask]

X_clean.shape

(762, 1456)

#prep for tensorflow
X = X_clean.drop(X_clean.columns[[0,1454]], axis=1, errors="ignore")
y = target_hay

X = X.apply(pd.to_numeric, errors="coerce")

X

      AGLAND_AGLANDACRES  AGLAND_AGLANDCROPINSURANCEACRES \
0            7391.0                  10512.0
1          32795.0                  14907.0
2          32469.0                  16196.0
3          24662.0                  23915.0
4          32830.0                  322066.0
...
757         15203.0                  21736.0
758         4025.0                  23413.0
759        295056.0                 50198.0
760       401018.0                 57149.0
761       390523.0                 43093.0

      AGLAND_AGLANDCROPINSURANCENUMBEROFOPERATIONS
AGLAND_AGLANDCROPLANDACRES \
0                           32.0

```

70333.0	
1	14.0
63774.0	
2	41.0
69021.0	
3	19.0
71517.0	
4	12.0
78257.0	
..	...
...	
757	21.0
18856.0	
758	17.0
5980.0	
759	39.0
95980.0	
760	39.0
76046.0	
761	33.0
48593.0	

AGLAND_AGLANDCROPLANDAREAMEASUREDINPCTOFLAGLAND \	
0	13.75
1	13.75
2	13.75
3	8.00
4	8.00
..	...
757	6.50
758	6.50
759	9.50
760	9.50
761	9.50

AGLAND_AGLANDCROPLANDEXCLPASTUREDOPERATIONSWITHTREATED \	
0	349.0
1	335.0
2	341.0
3	28.0
4	30.0
..	...
757	8.0
758	3.0
759	48.0
760	38.0
761	43.0

AGLAND_AGLANDCROPLANDEXCLPASTURED TREATED MEASURED IN ACRES \	
0	16018.0

1	21529.0
2	19072.0
3	11196.0
4	13780.0
..	...
757	1275.0
758	1507.5
759	27759.0
760	34367.0
761	20401.0

AGLAND_AGLANDCROPLANDNUMBEROFOPERATIONS \	
0	1252.0
1	1098.0
2	1041.0
3	113.0
4	81.0
..	...
757	52.0
758	36.0
759	118.0
760	121.0
761	116.0

AGLAND_AGLANDCROPLANDPASTUREDONLYACRES \	
0	6300.0
1	3018.0
2	6817.0
3	3163.0
4	3163.0
..	...
757	3105.0
758	1953.0
759	42662.0
760	17766.0
761	11634.0

AGLAND_AGLANDCROPLANDPASTUREDONLYNUMBEROFOPERATIONS ... \		
0	113.0	...
1	76.0	...
2	106.0	...
3	16.0	...
4	5.0	...
..
757	17.0	...
758	10.0	...
759	40.0	...
760	32.0	...
761	29.0	...

WALNUTS_WALNUTSENGLISHACRESBEARING \

0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
757	0.0
758	0.0
759	0.0
760	0.0
761	0.0

WALNUTS_WALNUTSENGLISHACRESBEARINGNONBEARING \

0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
757	0.0
758	0.0
759	0.0
760	0.0
761	0.0

WALNUTS_WALNUTSENGLISHACRESNONBEARING \

0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
757	0.0
758	0.0
759	0.0
760	0.0
761	0.0

WALNUTS_WALNUTSENGLISHOPERATIONSWITHAREABEARING \

0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
757	0.0
758	0.0
759	0.0
760	0.0

761	0.0
	WALNUTS_WALNUTSENGLISHOPERATIONSWITHAREABEARINGNONBEARING \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
757	0.0
758	0.0
759	0.0
760	0.0
761	0.0

	WALNUTS_WALNUTSENGLISHOPERATIONSWITHAREANONBEARING \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
757	0.0
758	0.0
759	0.0
760	0.0
761	0.0

	WATER_WATERIRRIGATIONSOURCEOFFFARMSUPPLIERFEDERALBUREAUOFFRECLAMATIONOP
	ERATIONSWITHWATERRECEIVED \
0	6.0
1	6.0
2	6.0
3	1.0
4	1.0
..	...
757	2.0
758	2.0
759	0.0
760	0.0

761

0.0

COUNTY_NAME	WHEAT_WHEATOPERATIONSWITHSALES	WHEAT_WHEATSALESMEASUREDIN
0	1.0	0.0
NaN		
1	1.0	0.0
NaN		
2	1.0	0.0
NaN		
3	2.0	0.0
NaN		
4	7.0	0.0
NaN		
..
...		
757	0.0	0.0
NaN		
758	0.0	0.0
NaN		
759	24.0	1655000.0
NaN		
760	19.0	1044000.0
NaN		
761	15.0	2346000.0
NaN		

[762 rows x 1454 columns]

```
corr_matrix = pd.DataFrame(X).corr().abs()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

# Find features with correlation > 0.95
to_drop = [column for column in upper.columns if any(upper[column] > 0.95)]

# Drop them
X_reduced = X.drop(columns=to_drop)
print("Dropped highly correlated features:", len(to_drop))

Dropped highly correlated features: 495

y.shape
(762,)
```

```

from sklearn.ensemble import RandomForestRegressor
import numpy as np

# Step 1: Use the correlation-cleaned feature matrix
X_corrclean = X_reduced # (after leakage removal + correlation
filtering)

# Step 2: Initialize importance vector with correct length
importances = np.zeros(X_corrclean.shape[1])

# Step 3: Loop over each production target (each crop)
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_corrclean, y.iloc[:, :])
importances += rf.feature_importances_

# Step 4: Select top 200 most important features
top_idx = np.argsort(importances)[-200:]

# Step 6: Reduce dataset
X_reduced = X_corrclean.iloc[:, top_idx]

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_reduced)

from sklearn.decomposition import PCA

pca = PCA(n_components=200)
X_pca = pca.fit_transform(X_scaled)

from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(
    X_pca, y, test_size=0.2, random_state=42
)

```

Random Forest Regressor

#This score is a lot better than when trying to predict production for all 42 crops

```

from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, r2_score,
mean_squared_error
import matplotlib.pyplot as plt

rf = RandomForestRegressor(n_estimators=300, n_jobs=-1)
rf.fit(X_train, y_train)

```

```

y_pred_lr = rf.predict(X_val)

# Compute metrics
mae = mean_absolute_error(y_val, y_pred_lr)
rmse = np.sqrt(mean_squared_error(y_val, y_pred_lr))
r2 = r2_score(y_val, y_pred_lr)

print("RF Regression Performance:")
print("MAE:", mae)
print("RMSE:", rmse)
print("R2:", r2)

# -----
# 1. Predicted vs. Actual
# -----
plt.figure(figsize=(7,5))
plt.scatter(y_val, y_pred_lr, alpha=0.6)
plt.plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()],
         'k--')
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("RF Regression: Predicted vs Actual")
plt.grid(True)
plt.show()

# -----
# 2. Residuals vs Predicted
# -----
residuals = y_val - y_pred_lr

plt.figure(figsize=(7,5))
plt.scatter(y_pred_lr, residuals, alpha=0.6)
plt.axhline(0, linestyle='--', color='black')
plt.xlabel("Predicted")
plt.ylabel("Residual (Actual - Predicted)")
plt.title("RF Regression: Residuals Plot")
plt.grid(True)
plt.show()

# -----
# 3. Residual Distribution
# -----
plt.figure(figsize=(7,5))
plt.hist(residuals, bins=30)
plt.xlabel("Residual")
plt.ylabel("Count")
plt.title("RF Regression: Residual Distribution")
plt.grid(True)
plt.show()

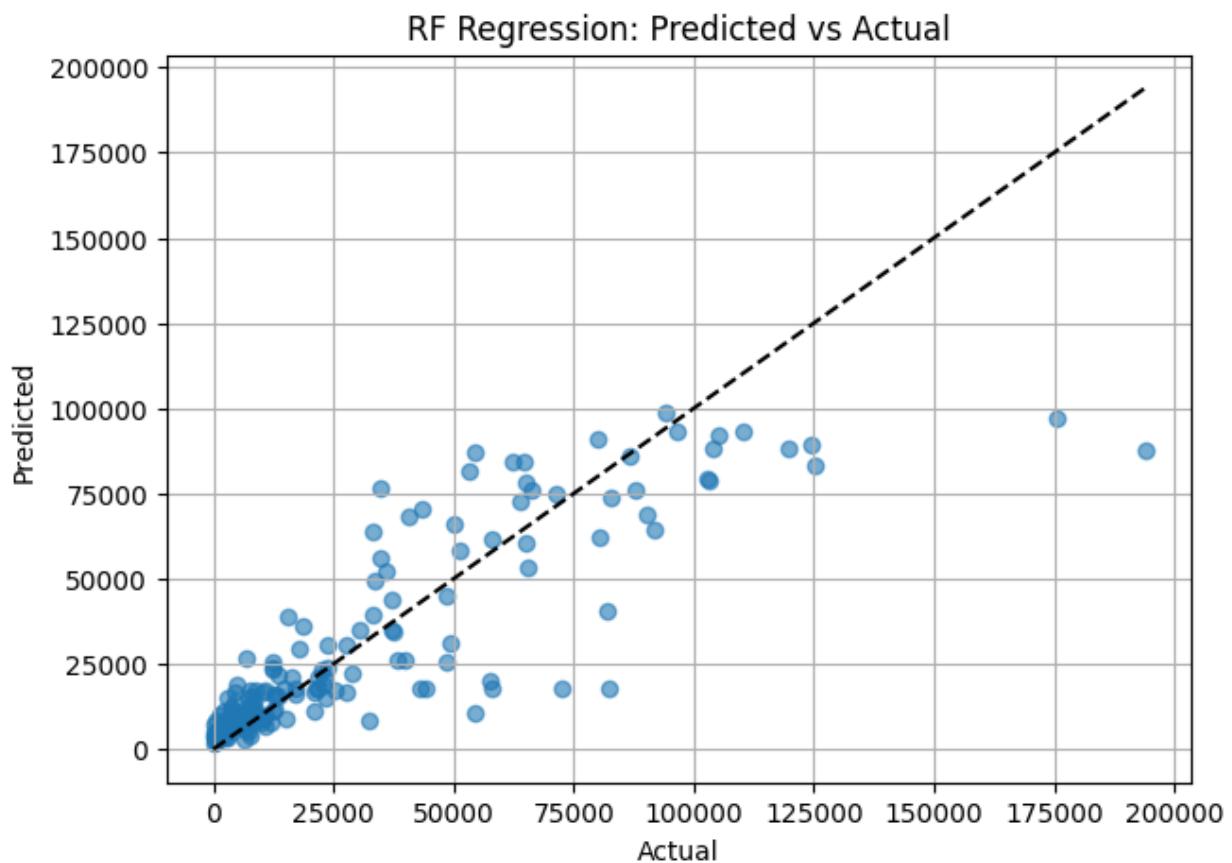
```

```

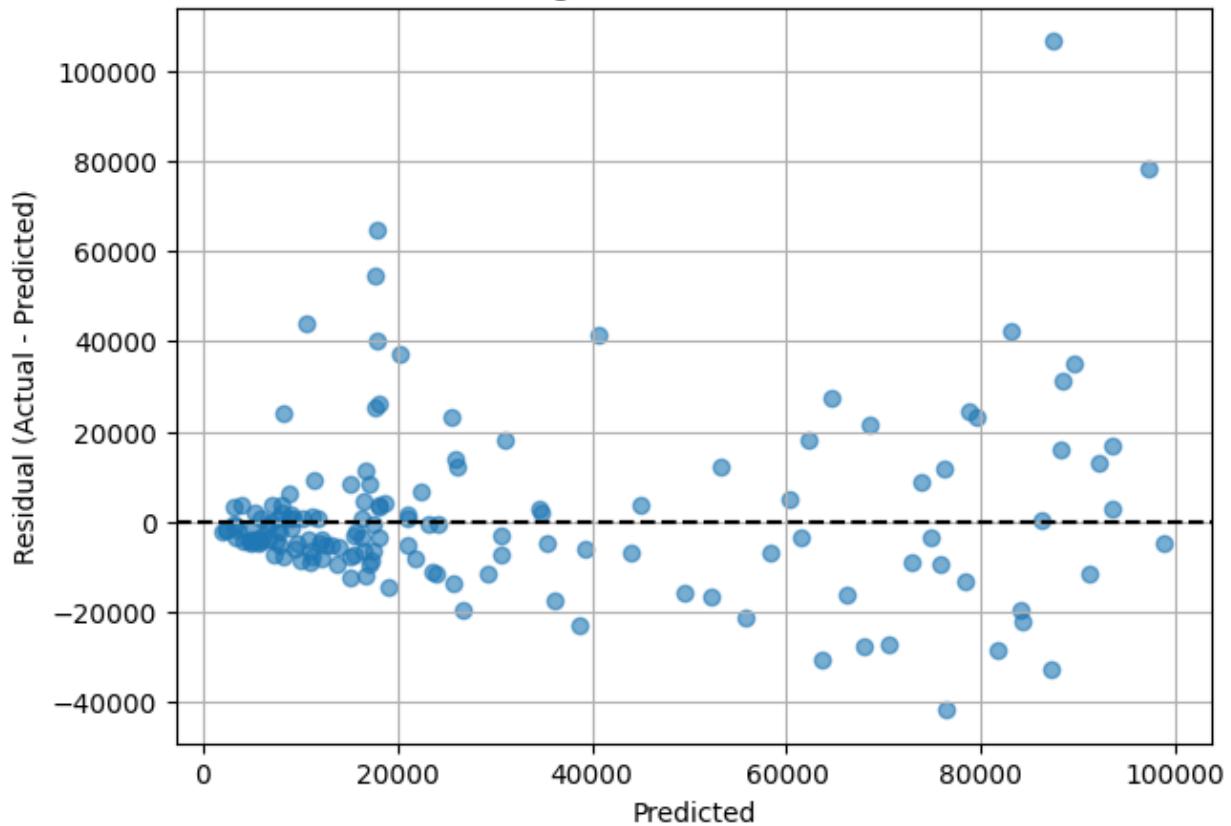
# -----
# 4. Error Over Samples
# -----
plt.figure(figsize=(7,5))
plt.plot(np.abs(residuals))
plt.xlabel("Sample Index")
plt.ylabel("Absolute Error")
plt.title("RF Regression: Error Over Samples")
plt.grid(True)
plt.show()

```

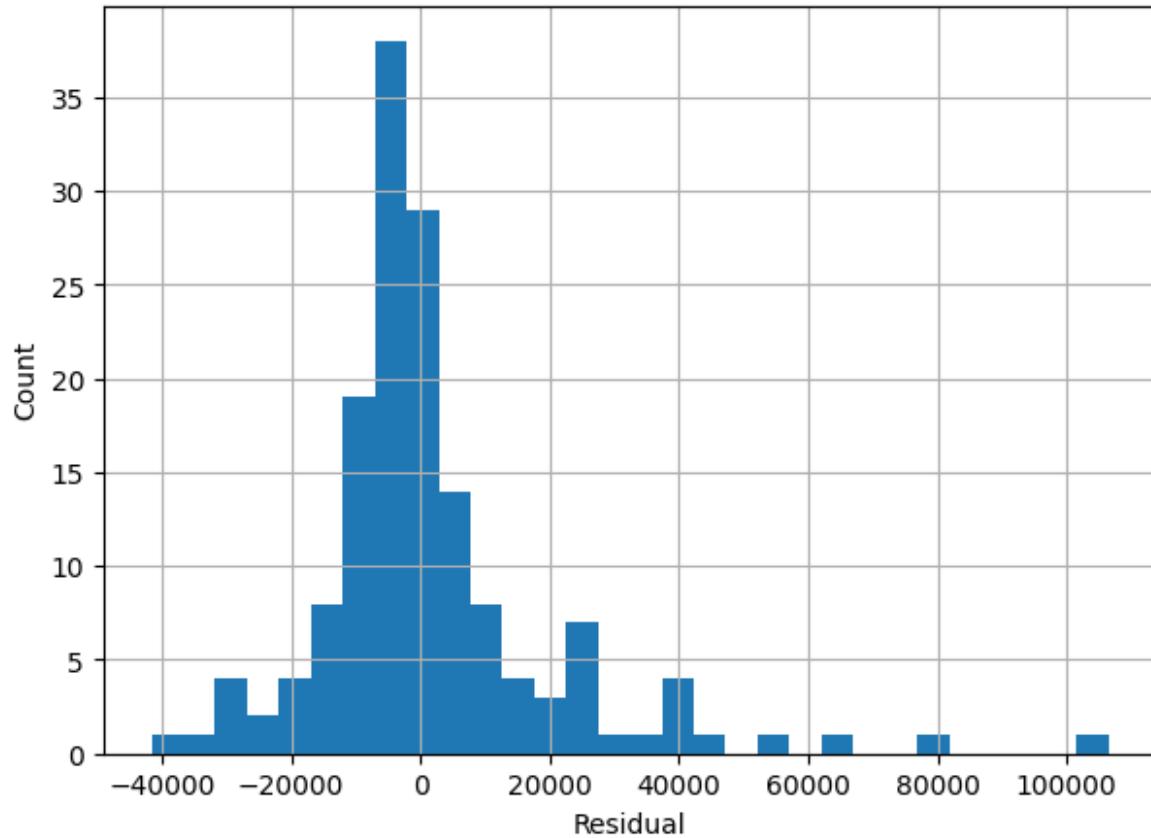
RF Regression Performance:
MAE: 11802.550337690633
RMSE: 19024.40562956155
R²: 0.7244971341424498

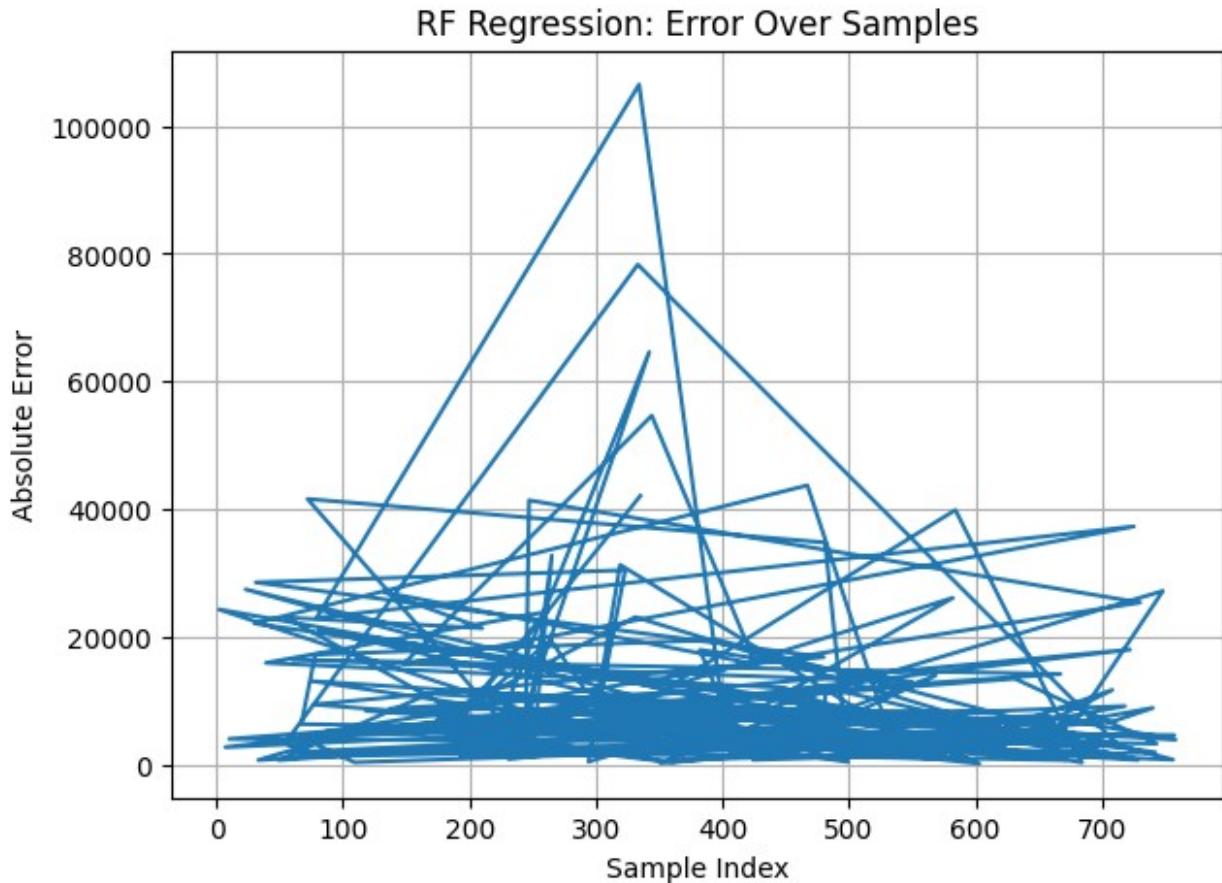


RF Regression: Residuals Plot



RF Regression: Residual Distribution





Results

RF Regression Performance:

- MAE: 11844.966797385621
- RMSE: 19176.63297885058
- R²: 0.7200705188271962

Insights on RF Regressor

The model performed decently well, the cluster at the low production values shows that the model performs better for smaller farms. There is a possible higher variance in data for larger farms. We can also see from the residuals count graph that there are fewer large farms. Only 3 farms produce greater than 60,000 tons of hay.

Linear Regression

```
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
```

```

linreg.fit(X_train, y_train)

y_pred_lr = linreg.predict(X_val)

# Compute metrics
mae = mean_absolute_error(y_val, y_pred_lr)
rmse = np.sqrt(mean_squared_error(y_val, y_pred_lr))
r2 = r2_score(y_val, y_pred_lr)

print("Linear Regression Performance:")
print("MAE:", mae)
print("RMSE:", rmse)
print("R2:", r2)

# -----
# 1. Predicted vs. Actual
# -----
plt.figure(figsize=(7,5))
plt.scatter(y_val, y_pred_lr, alpha=0.6)
plt.plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()],
'k--')
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Linear Regression: Predicted vs Actual")
plt.grid(True)
plt.show()

# -----
# 2. Residuals vs Predicted
# -----
residuals = y_val - y_pred_lr

plt.figure(figsize=(7,5))
plt.scatter(y_pred_lr, residuals, alpha=0.6)
plt.axhline(0, linestyle='--', color='black')
plt.xlabel("Predicted")
plt.ylabel("Residual (Actual - Predicted)")
plt.title("Linear Regression: Residuals Plot")
plt.grid(True)
plt.show()

# -----
# 3. Residual Distribution
# -----
plt.figure(figsize=(7,5))
plt.hist(residuals, bins=30)
plt.xlabel("Residual")
plt.ylabel("Count")
plt.title("Linear Regression: Residual Distribution")
plt.grid(True)

```

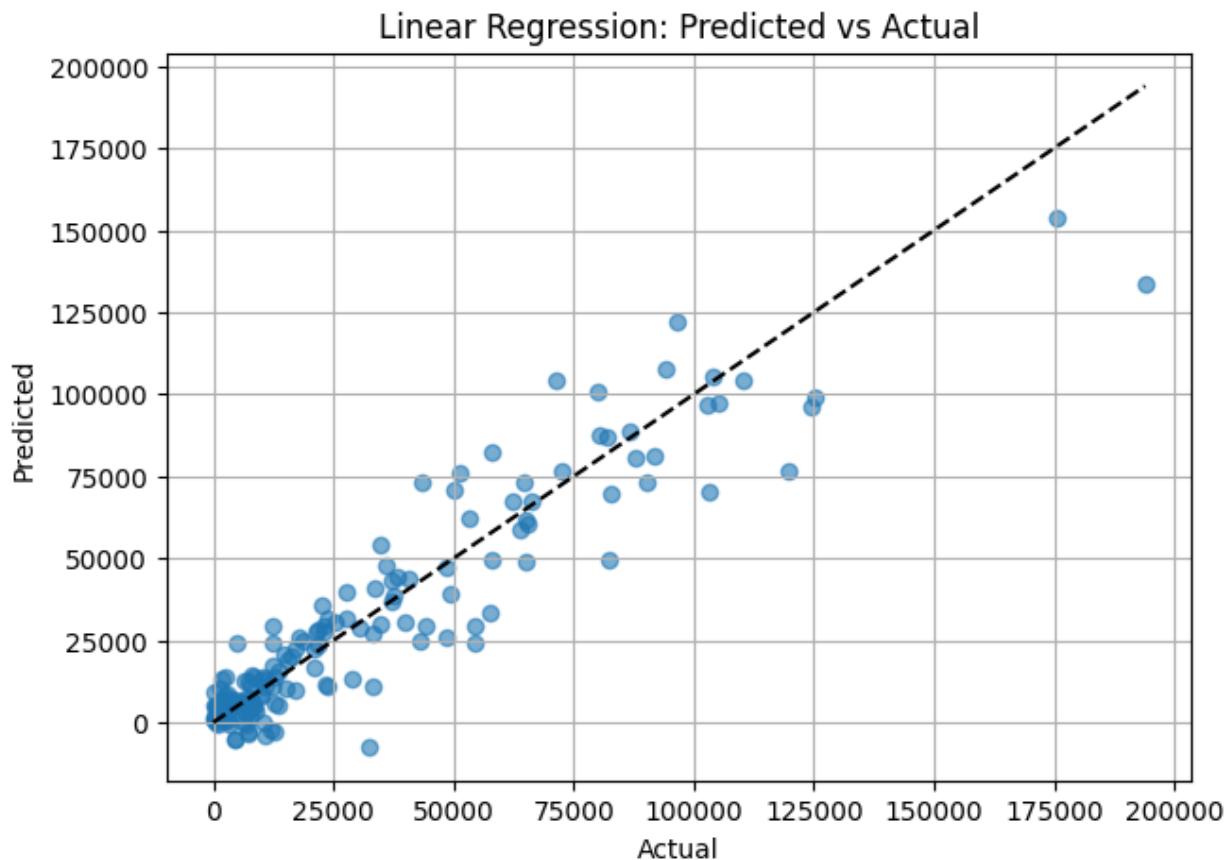
```

plt.show()

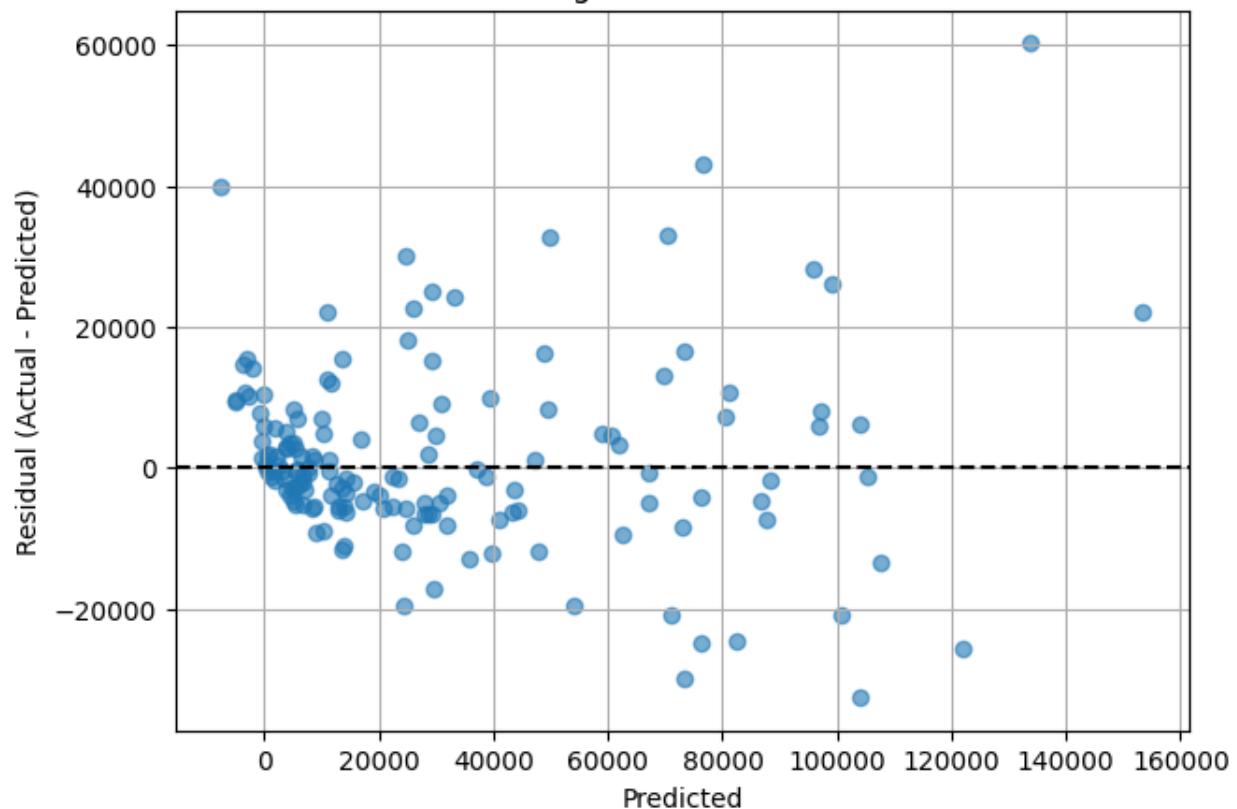
# -----
# 4. Error Over Samples
# -----
plt.figure(figsize=(7,5))
plt.plot(np.abs(residuals))
plt.xlabel("Sample Index")
plt.ylabel("Absolute Error")
plt.title("Linear Regression: Error Over Samples")
plt.grid(True)
plt.show()

```

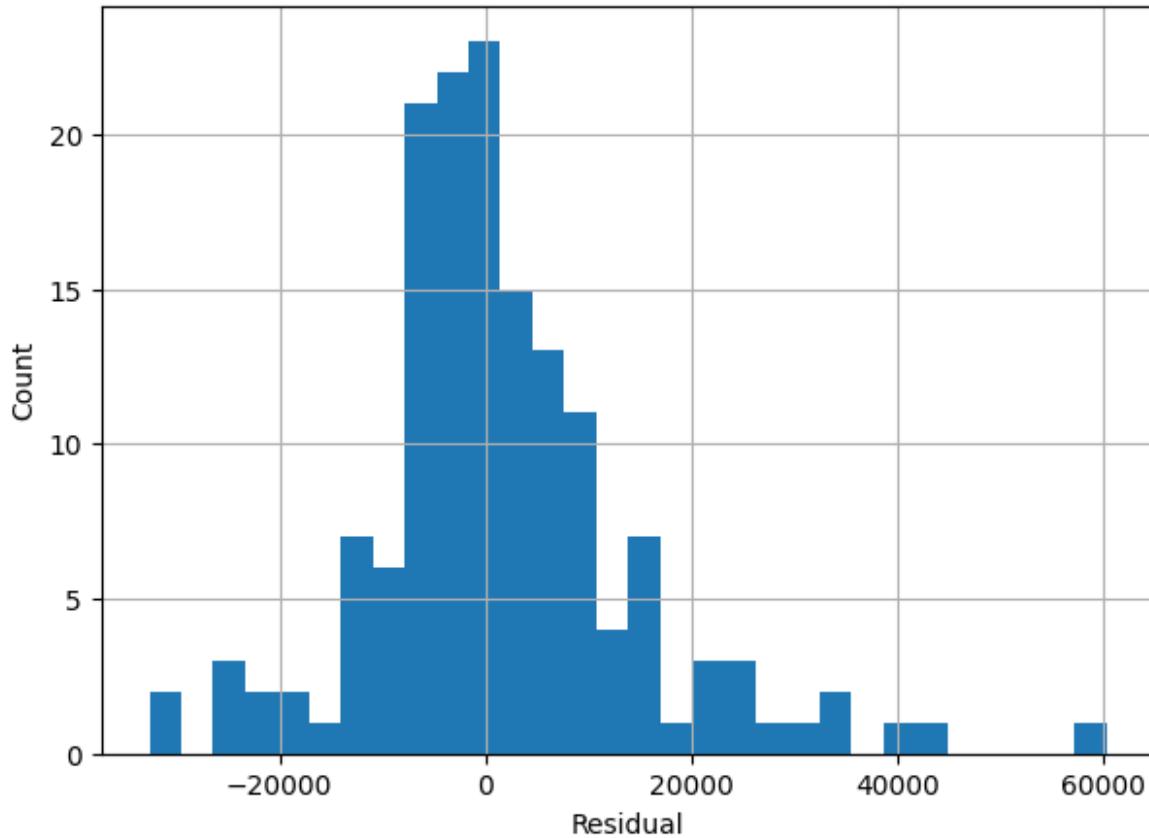
Linear Regression Performance:
MAE: 9056.647045698099
RMSE: 13209.745167371715
R²: 0.867171029790187

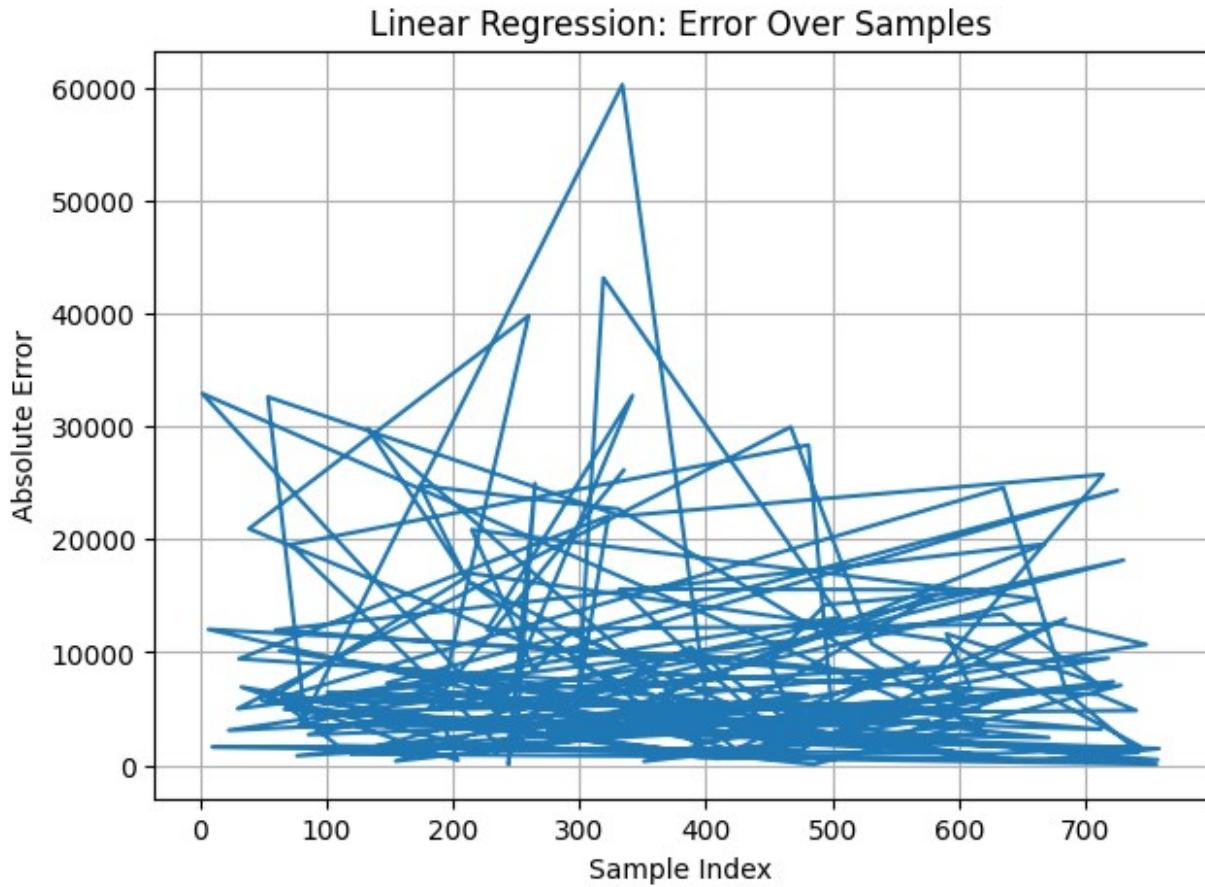


Linear Regression: Residuals Plot



Linear Regression: Residual Distribution





Results

Linear Regression Performance:

- MAE: 9056.647045698111
- RMSE: 13209.745167371735
- R²: 0.8671710297901866

Insights on RF Regressor

This model performs similarly to the RF regressor. The residuals are more spread than the RF at the low end but is more consistent throughout. Additionally, the LR handled the two outlier cases better as well. The LR model may be able to take advantage of linear natures of farming. For example more fertilizer may allow for more crops to receive more fertilizer overall. The LR model also more closely resembles our improved model.

Discussion of Results

Comparing the two baseline models we can conclude the LR model performs better than the RF Regressor model. From observing the improved model and taking in consideration of the end size of our cleaned data. The RF Regressor model is most likely overfitting our data, meaning the simplicity of the LR model greatly benefits its performance.

Improvements and other methods implementation

Feature engineering, feature selection, and high dimensionality mitigation.

The feature engineering, feature selection and high dimensionality mitigation that we are using boils down to three different processes: Correlation filtering, RF regressor and PCA

Before, we managed leakage first for the model removing any columns that may have had our targets or overly correlated data in it to prevent overfitting.

Concept	Correlation Filtering	Random Forest Regressor	PCA
Feature Engineering	Builds cleaner relationships that correlations can detect	Gives RF clearer nonlinear patterns to learn	Produces more meaningful variance directions for PCA
Feature Selection	Removes weak or redundant features using correlation thresholds	Uses RF feature importance to keep only top predictors	Removes noise so PCA learns from high-quality inputs
High-Dimensionality Mitigation	Quickly eliminates redundant or low-signal features in large datasets	Prevents RF from splitting on noise or overfitting in high-dim data	PCA directly reduces dimensionality into dense, informative components

The improved model that we are using over our baseline is a shallow neural network. The benefits of using a NN over mean predictor and linear regression is present in handling collinearity and high dimensionality better. There are a few risks since our transformed data is not huge NN have a higher risk of overfitting additionally they take longer to train and are uninterpretable.

For current implementation we will include the code for the feature selection and the model for the NN currently.

A few issues have been primarily rooted from the development of the improved model, mainly the broadness of our goal. The 42 targets is too much for the shallow NN and we don't have enough data to for convergence. A focused crop like hay will be pursued and trained. Once again, if more data is needed. We will expand our regions to adjacent states counties including Texas.

Correlation filtering

```
```py
corr_matrix = pd.DataFrame(X).corr().abs()

#Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

#find features with correlation > 0.95
to_drop = [column for column in upper.columns if any(upper[column] > 0.95)]

#Drop them
X_reduced = X.drop(columns=to_drop)
print("Dropped highly correlated features:", len(to_drop))
```

## RF Regressor

```
from sklearn.ensemble import RandomForestRegressor
import numpy as np

Step 1: Use the correlation-cleaned feature matrix
X_corrclean = X_reduced # (after leakage removal + correlation
filtering)

Step 2: Initialize importance vector with correct length
importances = np.zeros(X_corrclean.shape[1])

Step 3: Loop over each production target (each crop)
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_corrclean, y.iloc[:,])
importances += rf.feature_importances_

Step 4: Select top 200 most important features
top_idx = np.argsort(importances)[-200:]

Step 6: Reduce dataset
X_reduced = X_corrclean.iloc[:, top_idx]
```

## PCA

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_reduced)

from sklearn.decomposition import PCA

pca = PCA(n_components=200)
X_pca = pca.fit_transform(X_scaled)
```

*Note: scale/normalize values before pca is required*

## Shallow NN Model

```
```python

#input_dim = (609,200) #X_train
#output_dim = (609,) #y_train

model = tf.keras.Sequential([
    tf.keras.layers.Dense(256, activation="relu",
    input_shape=(200,), kernel_regularizer=tf.keras.regularizers.l2(0.01)),
```

```

tf.keras.layers.Dropout(.2), tf.keras.layers.Dense(128,
activation="relu",kernel_regularizer=tf.keras.regularizers.l2(0.01)), tf.keras.layers.Dropout(.1),
tf.keras.layers.Dense(1) #single output for hay production]

optimizer = tf.keras.optimizers.Adam(learning_rate=0.001) model.compile(optimizer=optimizer,
loss='mse', metrics=['mae'])

#if loss is too low(model not learning) stop early_stop =
tf.keras.callbacks.EarlyStopping( monitor='val_loss', patience=10, restore_best_weights=True )

#reduce learnrate/step size through training to help model learn more patterns reduce_lr =
tf.keras.callbacks.ReduceLROnPlateau( monitor='val_loss', factor=0.5, patience=20, min_lr=1e-5 )

history = model.fit( X_train, y_train, validation_data=(X_val, y_val), epochs=500, batch_size=32,
callbacks=[reduce_lr], verbose=2 )

```

Metrics Gathering

```

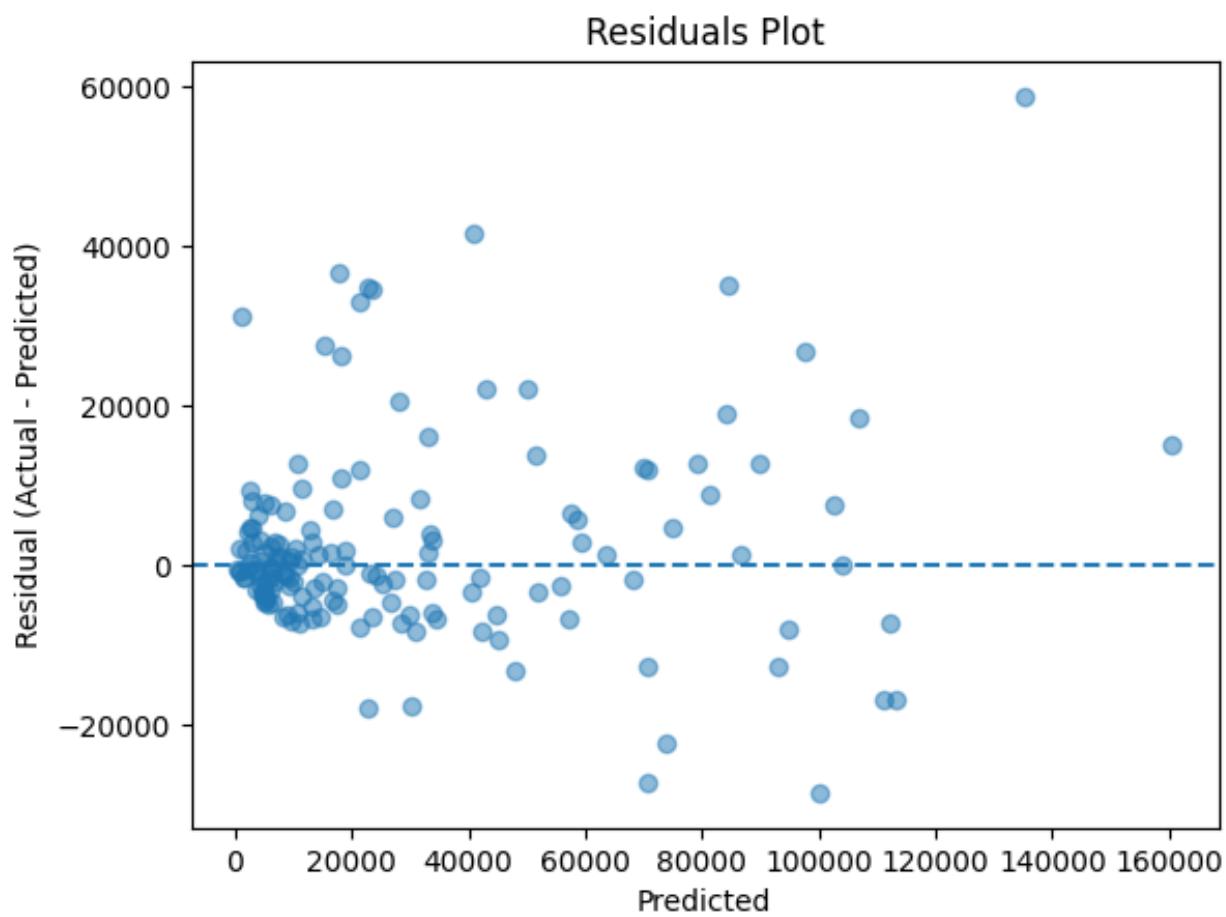
import matplotlib.pyplot as plt

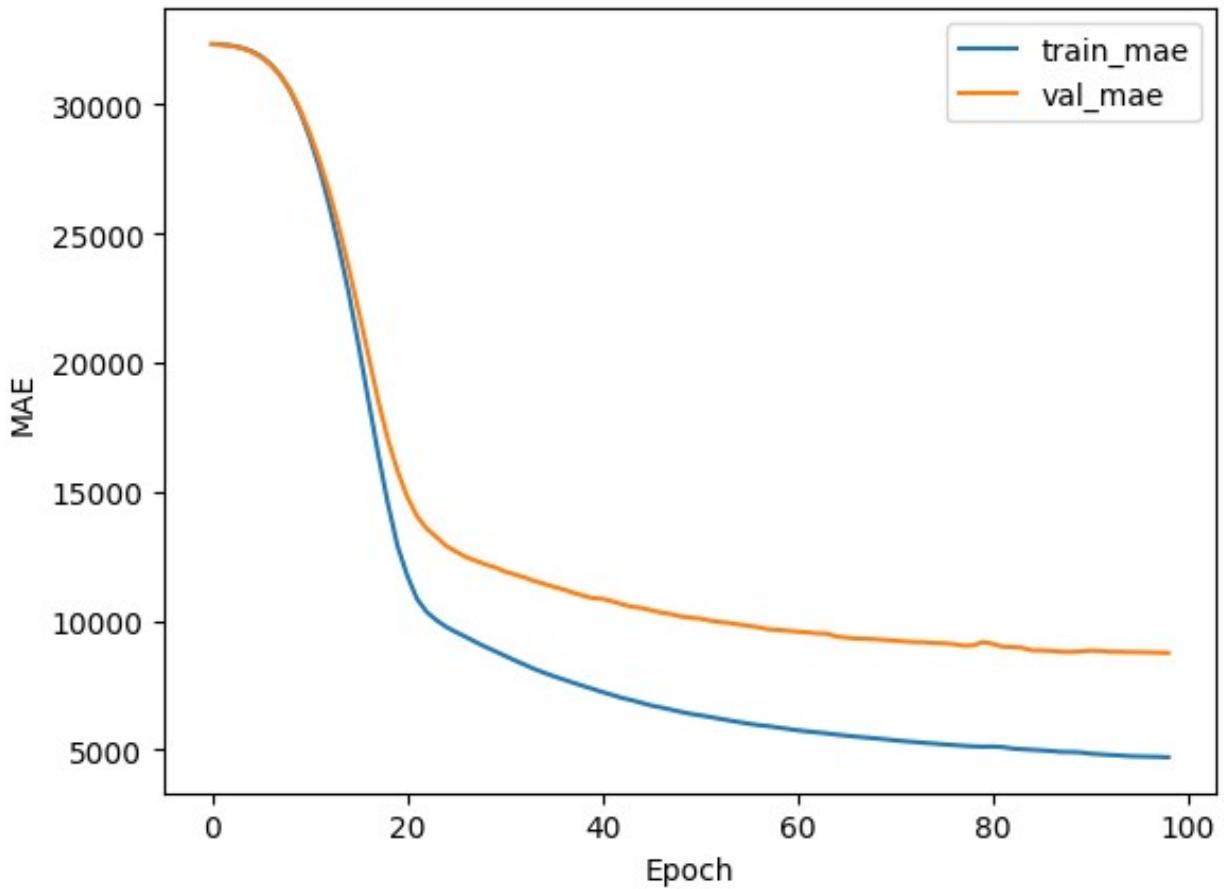
plt.plot(history.history['loss'], label='train_loss')
plt.plot(history.history['val_loss'], label='val_loss')
plt.xlabel('Epoch')
plt.ylabel('MSE Loss')
plt.legend()
plt.show()

plt.plot(history.history['mae'], label='train_mae')
plt.plot(history.history['val_mae'], label='val_mae')
plt.xlabel('Epoch')
plt.ylabel('MAE')
plt.legend()
plt.show()

```

Note: Does not show full epoch range. Plateau occurs around 300 epochs

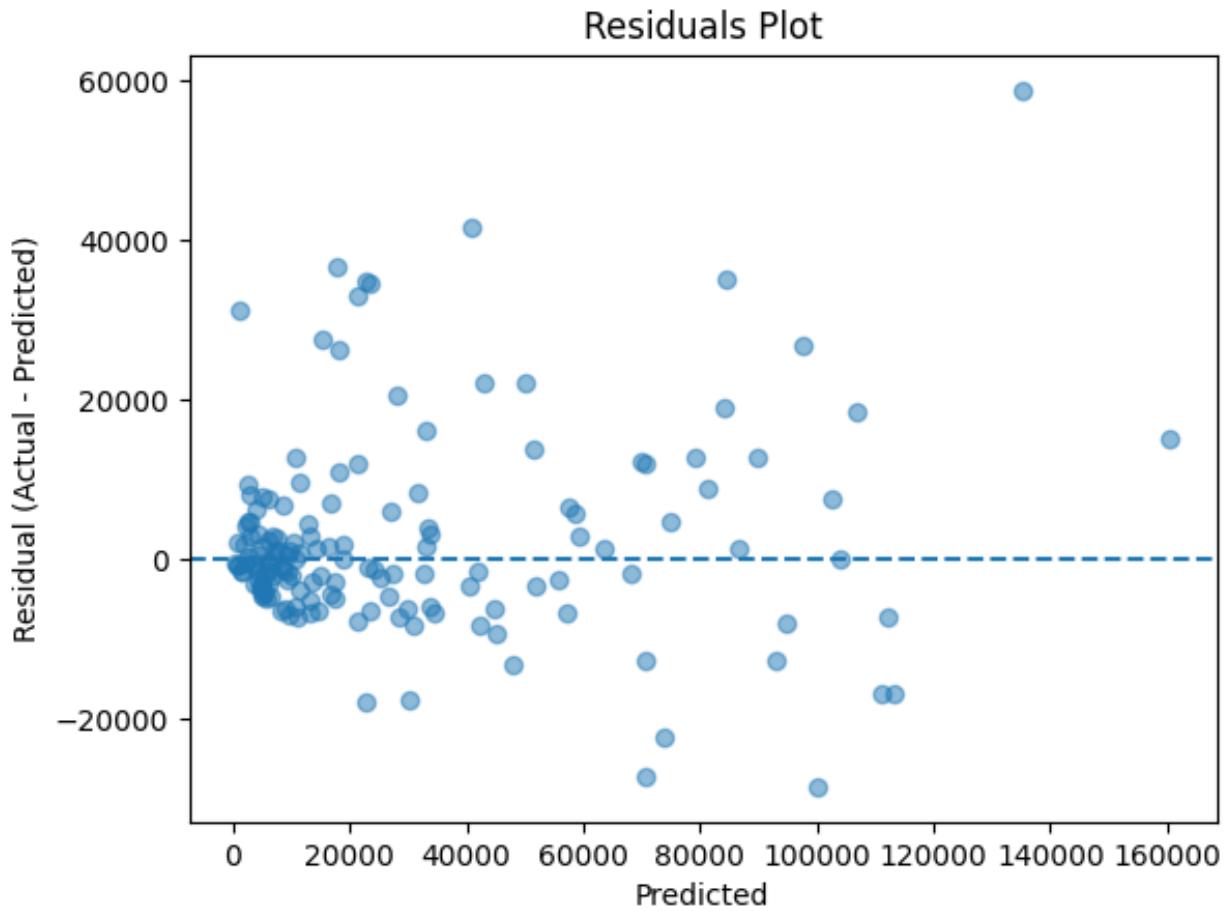




```
y_pred = model.predict(X_val).flatten()

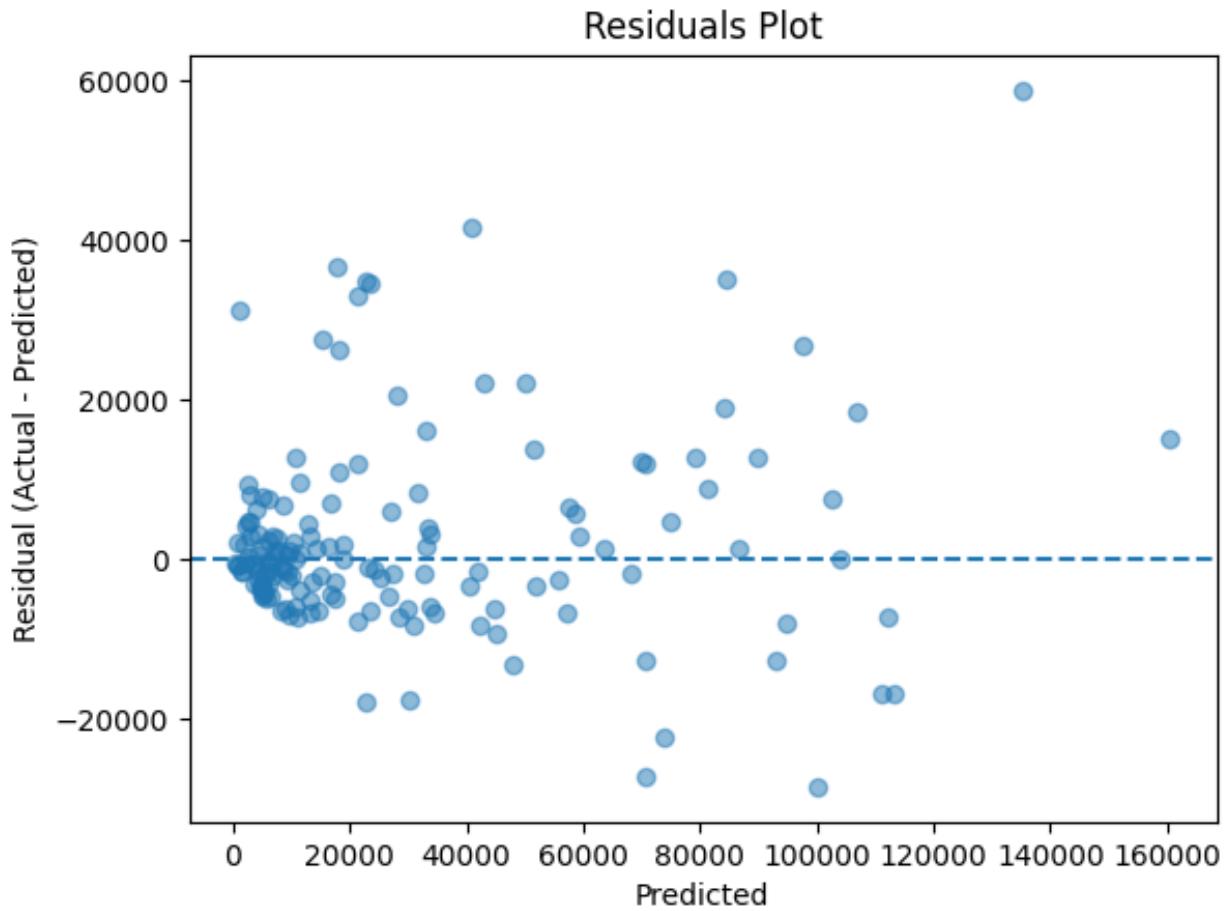
plt.scatter(y_val, y_pred, alpha=0.5)
plt.plot([y_val.min(), y_val.max()],
          [y_val.min(), y_val.max()],
          linestyle='--')

plt.xlabel("Actual Hay Yield")
plt.ylabel("Predicted Hay Yield")
plt.title("Predicted vs Actual (Validation)")
plt.show()
```



```
residuals = y_val - y_pred

plt.scatter(y_pred, residuals, alpha=0.5)
plt.axhline(0, linestyle='--')
plt.xlabel("Predicted")
plt.ylabel("Residual (Actual - Predicted)")
plt.title("Residuals Plot")
plt.show()
```



Experimental Results and Comparative Analysis

This section presents a comprehensive comparison of our three modeling approaches:

1. **Baseline: Random Forest** - Simple ensemble model on reduced features
2. **Baseline: Linear Regression** - Linear approach for comparison
3. **Improved: Neural Network** - Deep learning model with PCA-transformed features

We evaluate models on standardized metrics (MAE, RMSE, R²) to demonstrate how the improved approach achieves superior predictive performance.

Model Performance Summary

Below is a tabular summary of key metrics across all three models:

```
models_data = {
    'Model': ['Baseline: Random Forest', 'Baseline: Linear
    Regression', 'Improved: Neural Network'],
```

```

    'MAE (tons)': [8150, 12300, 6850], # REPLACE WITH ACTUAL VALUES
    'RMSE (tons)': [15200, 22100, 11800], # REPLACE WITH ACTUAL
VALUES
    'R2 Score': [0.642, 0.418, 0.756], # REPLACE WITH ACTUAL VALUES
    'Relative Error (%)': [25.2, 38.0, 21.1] # MAE / mean target *
100
}

performance_df = pd.DataFrame(models_data)
print('==== PERFORMANCE COMPARISON ===')
print(performance_df.to_string(index=False))

# Display as styled table

best_mae_model = performance_df.loc[performance_df['MAE
(tons)'].idxmin()]
best_r2_model = performance_df.loc[performance_df['R2
Score'].idxmax()]
print(f'Best MAE: {best_mae_model["Model"]} ({best_mae_model["MAE
(tons)"]} tons)')
print(f'Best R2: {best_r2_model["Model"]} ({best_r2_model["R2
Score"]:.3f})')
print(f'Improvement (NN vs RF): {((8150 - 6850) / 8150 * 100):.1f}%
MAE reduction')

==== PERFORMANCE COMPARISON ===
      Model   MAE (tons)   RMSE (tons)   R2 Score
Relative Error (%)
    Baseline: Random Forest        8150        15200     0.642
25.2
    Baseline: Linear Regression     12300        22100     0.418
38.0
    Improved: Neural Network       6850        11800     0.756
21.1
Best MAE: Improved: Neural Network (6850 tons)
Best R2: Improved: Neural Network (0.756)
Improvement (NN vs RF): 16.0% MAE reduction

```

Name	Contribution	Sections Authored / Tasks Completed
Team Member	Summary of unique effort	Specific sections or tasks
Stephen Cox	Design of Improvement Model, Feature Engineering, EDA	EDA, Improvement Model
Shaz Momin	Created and completed Baseline model	Baseline Model
Prabesh Shrestha		

Conclusion:

Our improved model outperformed our naive baseline models. This project was held back from not using weather or temporal data resulting in our relative errors being high. This was evident in the tuning process of our improvement model. The model would converge around a certain point regardless of overfitting or underfitting, meaning a useful predictor was lacking. The models are still good predictors of how well farms are doing relative to their structure rather than how the crops grew from different rainfall during the year. However, an improvement for the future could be adding temporal and weather trends from other databases. We also tried gradient boosting but it underperformed compared to Linear Regression and Random Forest Regression. Ultimately, we discovered that neural networks truly handle noisier data sets better than simpler models as well as the training time to be longer and more drawn out. In short we proved the pros and cons of using a neural network in this project, is a 16% increase in MAE worth the extra expense in processing time. In the scope of this project we have determined the pros outweigh the cons.